Ecological Indicators 102 (2019) 309–315

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Original Articles

Influential factors on water footprint: A focus on wheat production and consumption in virtual water import and export regions

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ARTICLE INFO

Keywords:
Production water footprint
Consumption water footprint
Water import
Water export
Multivariate regression model

ABSTRACT

Agriculture is a key sector and a major consumer of water resources; therefore, a clear understanding of the agricultural water demand for crop production and consumption is imperative for addressing water scarcity problems, particularly in water export regions. This study provides new insights into the influential factors driving the changes in the agricultural production water footprint (WF_{prod}) and consumption water footprint (WF_{con}) in the net water import and net water export regions. The WF_{prod} and WF_{con} of wheat are evaluated in Beijing city (the net water import region) and Heilongjiang province (the net water export region) over the period 1996–2015. The statistical significances of the influential factors, i.e., climate change, gross domestic product, population, dietary demand and technology update are determined using a multivariate linear regression model (LRM) and nonlinear regression model (NLRM). The results indicate that the gross domestic product and population were the dominant positive influential factors, whereas technology update and dietary demand were the dominant negative influential factors affecting the changes in the WF_{prod} and WF_{con} in the net water import region. In the net water export region, technology update was the dominant negative influential factor affecting the changes in the WF_{prod} and WF_{con}. Climate change did not contribute significantly to the changes in the WF_{prod} and WF_{con} of wheat; however, it was an important factor (especially precipitation for the green WF with an average relative importance of more than 22% and the blue WF with an average relative importance of more than 15%) affecting the changes in the WF_{prod} and WF_{con} of the crop. An in-depth analysis of the influential factors that contribute to the changes in the WFs is fundamentally important for decision-makers to develop countermeasures and strategic planning implementations to mitigate water resource pressure in China.

1. Introduction

Agricultural water demand has shown a noticeable increasing trend around the world and accounts for 90% of global water consumption (Hoekstra and Mekonnen, 2012). The main influential factors for this trend were rapid economic development, population explosion, improvement of living standards, expansion of the agricultural sector, and climate change (Mo et al., 2016; Zhuo et al., 2016a; Tamea et al., 2014). Recently proposed solutions to meet the increasing agricultural water demand include the development of nonconventional water resources and virtual water trade (Dalin et al., 2015; Zhuo et al., 2016b; Ye et al., 2018). The virtual water content (VWC) is defined as the amount of water required for the production of goods and services along the supply chains and the virtual water trade refers to the trade in water resources, which are virtually embedded in the traded commodities (Allan, 1998). Trade in water-intensive commodities has generated water savings for the import regions and relieved the pressure on their own water resources; however, trade has also increased water use in the export regions (Dalin et al., 2014). This situation exacerbates water stress for virtual water export regions and causes the local population to suffer from increased water scarcity. Therefore, it is critical to clearly understand the unique effects of various factors on the water demand for the production and consumption of agricultural products in water import and export regions, for the purposes of water scarcity alleviation and water resources management.

Water footprint (WF), based on the concept of the VWC, is an indicator of water use related to production or consumption in the economy (Hoekstra, 2003). The WF of crop production measures the

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https://doi.org/10.1016/j.ecolind.2019.02.051
Received 19 June 2018; Received in revised form 18 February 2019; Accepted 22 February 2019
Available online 28 February 2019
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consumption of rainfall over croplands during the crop's growing period (the green WF), the consumption of surface and underground water as a result of irrigation (the blue WF), and the water pollution resulting from leaching and runoff of fertilizers and pesticides from croplands (the grey WF) (Hoekstra et al., 2011; Hoekstra, 2013). The green and blue WFs together are called the consumption WF (WF_{con}). The WF_{con} in a region consists of internal and external components. The internal WF refers to the part of the WF that is used in the region for the production of products that are consumed locally (here, the internal WF is called the production WF, WF_{prod}). The external WF refers to the part of the WF that is used in other areas for creating products that are imported and consumed in the region (Hoekstra et al., 2011).

Recently, some studies have investigated the influence of various factors on the agricultural WF and the virtual water trade. One important study is by Zhao and Chen (2014), who explored the driving forces behind changes in the agricultural WF_{con} by decomposing the factors that affected the changes in China's agricultural WF_{con} into the diet structure, efficiency, agricultural economic activity, and population effects. The authors provided a useful framework for analyzing the driving forces of the agricultural WF_{con} in water import regions and determined that economic activity was the largest positive contributor to increase in the WF_{con}, whereas water efficiency improvement was the most significant factor affecting a decrease in the WF_{con}. Due to the large water consumption for the production of crops and the opposite impacts of water trade on water import and export regions, an analysis of the difference in the driving forces of the WF_{prod} and WF_{con} between water import regions and export regions should be conducted to improve our current understanding. Tamea et al. (2014) identified the significant drivers of virtual water import and export for each country in the world and focused on changes in the population, gross domestic product, arable land, the WF of agricultural production and dietary demand, and the geographical distance between countries. Nowadays, climate change and its impact have major impacts on water resources and crop production in China (Piao et al., 2010). Precipitation changes directly influence the green WF of agricultural products and indirectly affect irrigation water consumption (blue WF). Moreover, increasing frequencies of climate extremes such as floods and droughts will affect the growing conditions of crops and may cause economic losses. Therefore, climate change has to be included in any study on future water resources, in addition to various socio-economic factors.

There is a current lack of studies providing comprehensive analyses of the effects of climate, economy and society on the agricultural water demand for virtual water import and export regions. Therefore, the objective of this study is to provide new insights into the influential factors driving the changes in the agricultural WF_{prod} and WF_{con} in water import and water export regions, respectively. The WF_{prod} (including green production WF, $WF_{prod\ green}$, and blue production WF, $WF_{prod\ blue}$) and WF_{con} (including green consumption WF, $WF_{con\ green}$, and blue consumption WF, $WF_{con\ blue}$) of wheat are evaluated for Beijing city (water import region) and Heilongjiang province (water export region) during 1996–2015. The statistical significances of the influential factors, i.e., climate change, gross domestic product, population, dietary demand, and technology update, are determined using a multivariate linear regression model (LRM) and nonlinear regression model (NLRM). The results provide guidance for agricultural water resources management in water import and export regions to improve the long term resiliency and sustainability.

2. Methods

2.1. Study area

Beijing city and Heilongjiang province were selected as the water import and export regions, respectively (Fig. S5). As the largest urban region and economic center of northern China, Beijing has to feed 21.7 million residents and a large transient population (BMBS, 2016). Due to limited arable land resources, almost all crops and livestock products produced in Beijing are supplied to local consumers (Huang et al., 2012). However, the local products cannot meet the large demand for food for the entire population and only accounted for about 17% of total grain crop consumption and 23% of total livestock product consumption in 2014 (FAO, 2014; BMBS, 2015). Thus, Beijing needs to import a large number of primary products from other regions to meet the local food demand and this involves the virtual water trade embedded in the products. The virtual water import volume of Beijing exceeded 7.26 million m^3 in 2007, in particular, around 90% of the virtual water import was from agricultural sectors (Dong et al., 2014). Heilongjiang province is located in the northern part of mainland China and receives an annual precipitation of 420.1 mm in 2015 (75.7% of precipitation occurs during June, July, August and September) (HMBS, 2016). Heilongjiang has 25% of the national agricultural land, accounting for 22% of the national grain demand in 2012 (FAO, 2012; NBSC, 2013; HMBS, 2013). The export volume of rice was more than 40 thousand tons, with a turnover of 30.92 million US dollars in 2012 (HMBS, 2013). Agricultural water consumption contributed 78.3% of the total water consumption in Heilongjiang. However, the water use efficiency and productivity in Heilongjiang were relatively low due to irrational irrigation methods and structures (Dalin et al., 2014). The region's surface and groundwater resources were further threatened by a projected drought and by the development of the water-intensive coal industry. Water scarcity is also a considerable problem in this water export region.

2.2. Calculation of WF_{prod} and WF_{con}

Wheat was selected as the crop in this study for the implementation of the methods. A series of 20-year (1996–2015) WF_{prod}, $WF_{prod\ green}$, $WF_{prod\ blue}$, and WF_{con}, $WF_{con\ green}$, $WF_{con\ blue}$ of wheat in Beijing and Heilongjiang province were evaluated.

The WF_{prod} (m^3/ton) of the crop was calculated by dividing the total green and blue evapotranspiration (ET, m^3/ha) during the crop's growing period by the crop yield (Y, ton/ha) (Ye et al., 2018; Dalin et al., 2014; Hoekstra et al., 2011). This represented crop water consumption.

$$WF_{prod} = \frac{ET}{Y} \tag{1}$$

The daily ET and Y were simulated with the Food and Agriculture Organization (FAO) crop water productivity model AquaCrop (Steduto et al., 2009; Raes et al., 2009; Hsiao et al., 2009). In AquaCrop, the daily crop transpiration (Tr, mm) was used to derive the daily gain in above-ground biomass (B) based on the normalized biomass water productive of the crop, which was normalized for carbon dioxide (CO_2) concentration of the bulk atmosphere, the evaporative demand of the atmosphere (ET_0), and the crop classes. The harvestable portion (the crop yield) of the B at the end of the growing period was determined as the product of the B and the harvest index. The harvest index was adjusted to the water stress depending on the timing and extent of the stress (Steduto et al., 2009; Raes et al., 2009; Hsiao et al., 2009). The simulated Y of each crop was consistent with that in the Beijing and Heilongjiang province statistics.

The WF_{con} (m^3/ton) was accounted on the base of a bottom-up approach, by multiplying the product consumption volume of the regional population by the corresponding WF:

$$WF_{con} = \frac{P \times WF_{prod} + I \times WFi_{prod}}{P + I} \tag{2}$$

where P is the final consumption of the local agricultural products, I is the final consumption of the imported agricultural products. WF_{prod} is the local WF of the crop and WFi_{prod} is the national average WF of the imported crop. Here it was assumed that the external WF (i.e., the WF that is used in other areas for creating products that are imported and

consumed in the importing region) excluded the WF from other countries due to data availability.

2.3. Multivariate and regression analysis

In this study a multivariate regression analysis was conducted using the JMP Pro 12® and R software (Team, 2014) to determine the relationships between the WFs (WF_{prod}, $WF_{prod\ green}$, and $WF_{prod\ blue}$ for crop production; WF_{con}, $WF_{con\ green}$, and $WF_{con\ blue}$ for crop consumption) and seven influential factors (average minimum temperature (T_{min}), average maximum temperature (T_{max}), and total precipitation (P) for climate change indicators, gross domestic product (GDP), population (Pop), annual per-capita dietary demand (D), and yield per unit area for technology update (Y_{unit})). First, a pairwise method was used to estimate the Pearson correlation coefficient (r) between the WFs and the influential factors, with values closer to 1 or −1 indicating stronger positive or negative correlation, respectively. Then, a regression analysis was performed to identify the potential influence and the effects of the influential factors on the WFs. A LRM and a NLRM were used. The LRM is defined as:

$$WF = \alpha_0 + \alpha_1 \cdot v_1 + \alpha_2 \cdot v_2 + \ldots + \alpha_7 \cdot v_7 \quad (3)$$

where v_1–v_7 are the influential factors affecting the WFs and α_0–α_7 are the linear regression parameters. The NLRM is defined as:

$$WF = \beta_0 \cdot v_1^{\beta_1} \cdot v_2^{\beta_2} \cdot \ldots \cdot v_7^{\beta_7} \quad (4)$$

where β_0–β_7 are the nonlinear regression parameters. The uncertainties of the fitted model were examined by determining: the p-value, the R^2 value, and the relative error (e). The p-value indicates the observed significance level of the influential factor affecting the WFs. The R^2 value represents the proportion of variation in the WFs that is explained by the influential factors. The e value reflects the suitability of the model in different regions; a lower e value indicates better suitability in other regions. A relative importance (RI) analysis was also performed to examine the contribution of each influential factor variable to the WFs using a dominance analysis method (Kruskal, 1987; Lindeman et al., 1980) and decomposition method (Genizi, 1993).

3. Results

3.1. Multivariate and regression analysis model for WF_{prod}

Fig. 1 illustrates the multivariate analysis results for the different types of WF_{prod} of wheat in Beijing. The $WF_{prod\ green}$ represents the direct consumption of rainfall during the crop's growing period and it had the strongest positive correlation with P (r = 0.69). Pop and GDP had the second and third highest positive correlations with $WF_{prod\ green}$. D and Y_{unit} had negative correlations with $WF_{prod\ green}$. The climate indicators, T_{min} and T_{max}, had low correlations with the $WF_{prod\ green}$ because its growing period is in the winter and spring when the ET of green water and blue water were both low. For the same influential factors, the correlation coefficients differed for $WF_{prod\ blue}$ and $WF_{prod\ green}$. P had the largest negative correlation with $WF_{prod\ blue}$ for wheat (r = -0.77). T_{min} and T_{max} had low correlations with $WF_{prod\ blue}$ but T_{max} had a stronger relationship than T_{min}. D and Y_{unit} also showed a high negative correlation with $WF_{prod\ blue}$. A higher Y_{unit} indicated higher water use productivity and the total blue water was lower in this case. The WF_{prod} of wheat also showed very strong correlations with Y_{unit} for the same reason as mentioned for $WF_{prod\ blue}$. The other influential factors, i.e., Pop, GDP, T_{min} and T_{max}, all had low correlations with the WF_{prod} of wheat in the study areas (r < 0.6).

Fig. 2a and b summarize the results of the LRM and NLRM for wheat in Beijing. The R^2 values of the regression models for the WFs were all less than 0.9. This was attributed to the long growing period of wheat (around 250 days in Beijing) and the fluctuating environmental and social conditions. The RI values of the factor P in regression models were highly significant for the $WF_{prod\ green}$ and $WF_{prod\ blue}$. In particular, the RI of P for $WF_{prod\ green}$ was 43.97% in the LRM. The RI values of GDP and Pop for the WF_{prod} and $WF_{prod\ green}$ (but not for the $WF_{prod\ blue}$) were significant in the two regression models. Y_{unit} exhibited a low contribution to the WF_{prod}, $WF_{prod\ green}$ and $WF_{prod\ blue}$ in the two regression models. Another noteworthy result was the high contribution of T_{max} to the $WF_{prod\ blue}$ in the two regression models (RI = 15.26% for the LRM and 17.97% for the NLRM).

In summary, the different types of WF_{prod} of wheat in the water import regions were significantly influenced by P, GDP, and Pop (Table 1). P exhibited a positive contribution to $WF_{prod\ green}$ and a negative contribution to $WF_{prod\ blue}$. GDP and Pop exhibited positive contributions to the WF_{prod}. There were no consistent contributions from the other influential factors to the WFs of wheat in this study.

In water export regions, crop production and supply are the first priority for the agricultural sector not only for local demand but also for outside trade. Thus, an understanding of the driving factors for the WFs of the crop production should be a priority in these regions; however, few studies have determined the driving factors for the WF_{prod} in the water export regions. The WF_{prod} in the water export regions were influenced significantly by technology update (Table 1, Figs. S1 and S2). Technology update contributed negatively to all the WF_{prod}. The other

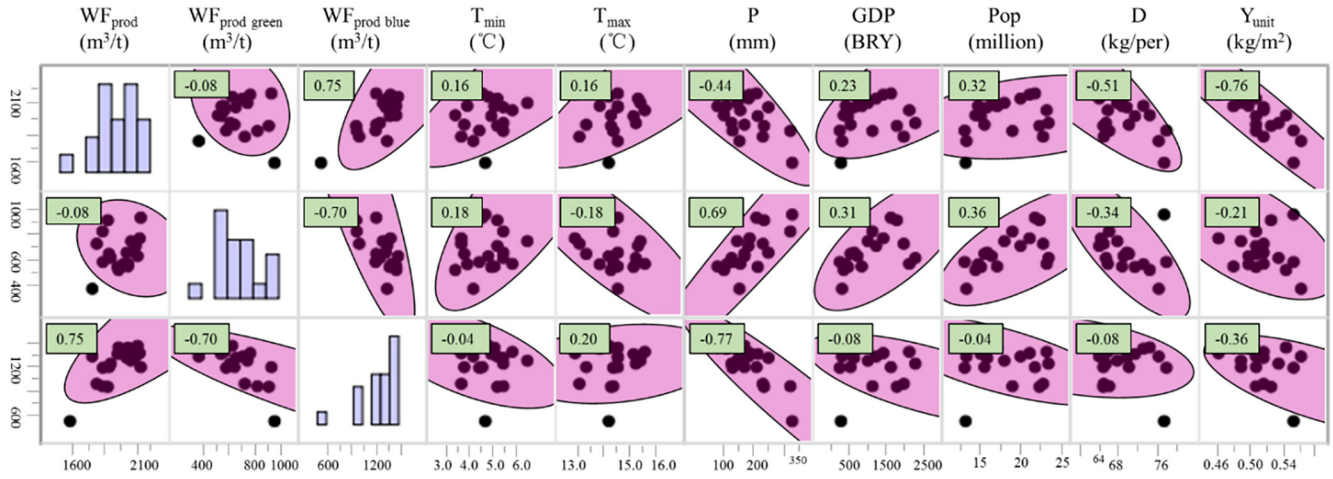

Fig. 1. Correlations between the WF_{prod} of wheat (WF_{prod}, $WF_{prod\ green}$ and WF_{prod}) and seven influential factors (average minimum temperature (T_{min}), average maximum temperature (T_{max}) and total precipitation (P) for climate change indicators, gross domestic product (GDP), population (Pop), annual per-capita dietary demand (D), and yield per unit area for technology update (Y_{unit})) in Beijing. The numbers in the green boxes are the correlation coefficients (r) of the two variables.

a.

	T_{min} (℃)	T_{max} (℃)	P (mm)	GDP (BRY)	Pop (million)	D (kg/capita)	Y_{unit} (kg/m^2)	Int.	R^2
WF_{prod} (m^3/t)	-17.231** RI=1.19%	56.439** RI=5.21%	-0.811** RI=5.88%	-0.502** RI=38.33%	112.322* RI=40.90%	1.685*** RI=0.98%	-2360.512** RI=7.52%	1076.672*	0.83
$WF_{prod\ green}$ (m^3/t)	120.684** RI=4.17%	-66.572** RI=3.08%	1.197** RI=43.97%	-0.835** RI=31.91%	241.073** RI=12.02%	41.251** RI=4.35%	-318.238* RI=0.50%	-4933.496**	0.75
$WF_{prod\ blue}$ (m^3/t)	-93.831** RI=11.14%	96.091** RI=15.26	-2.057*** RI=25.62%	-0.074** RI=9.63%	-15.334*** RI=9.59%	-19.135** RI=19.14%	-1761.134* RI=9.63%	3231.095**	0.76

b.

	T_{min} (℃)	T_{max} (℃)	P (mm)	GDP (BRY)	Pop (million)	D (kg/capita)	Y_{unit} (kg/m^2)	Int.	R^2
WF_{prod} (m^3/t)	-0.116** RI=3.59%	0.627* RI=7.89%	-0.070* RI=4.84%	-0.199** RI=34.78%	0.458** RI=19.41%	-1.010* RI=13.25%	-1.132*** RI=16.24%	21330.45***	0.87
$WF_{prod\ green}$ (m^3/t)	1.127* RI=8.41%	-2.537* RI=7.69%	0.200** RI=38.92%	-0.927** RI=31.25%	3.063** RI=9.99%	-2.581** RI=3.33%	-0.140* RI=0.40%	1.738E08*	0.73
$WF_{prod\ blue}$ (m^3/t)	-0.694** RI=13.99%	2.198** RI=17.97%	-0.288* RI=12.97%	0.085** RI=9.64%	-0.779** RI=21.44%	-1.073* RI=11.20%	-1.682** RI=12.78%	6486.344**	0.69

Fig. 2. Results of the (a) linear regression analysis and (b) nonlinear regression analysis showing the statistically significant factors for the WF_{prod}, $WF_{prod\ green}$ and $WF_{prod\ blue}$ in Beijing. The green numbers represent the coefficients in the regression equations of the influential factors in the column. Significance levels: *** > 99%; ** 95–99%; * 90–95%. The "RI" values are the relative importance values of each selected factor variable of each WF.

influential factors did not exhibit consistent contributions to the WF_{prod} for wheat in this study. The details of the results are described in *Driving influential factors for WFprod in the net water export region*, Supporting Information.

3.2. Multivariate and regression analysis model for WF_{con}

The driving factors for WF_{con} were the main focus of previous studies, which have considered the factors of GDP, population, dietary demands, etc. (Tamea et al., 2014; Zhao and Chen, 2014; Zhao et al., 2014). Climate change was for the first time considered in this study to conduct a comprehensive analysis of the influences on the WF_{con}.

Fig. 3 illustrates the multivariate analysis results for the different types of WF_{con} of wheat in Beijing. *P* exhibited a high correlation with the $WF_{con\ green}$ and $WF_{con\ blue}$; however, unlike for the WF_{prod}, the factor was not the most significant one. *GDP* and *Pop* were the top positive influential factors with the highest correlation coefficients for the WF_{con}, $WF_{con\ green}$ and $WF_{con\ blue}$ of wheat in Beijing. *D* had a strong negative correlation with WF_{con}, $WF_{con\ green}$ and $WF_{con\ blue}$.

The significant influential factors for the WF_{con} of wheat were determined by the regression models and RI analysis (Fig. 4a and b). Overall, the R^2 values were lower for the NLRM than the LRM, which indicated that the influential factors affecting the change in the WF_{con} of wheat were more clearly described by the LRM due to the linear bottom-up evaluation approach. *Pop* and *GDP* were the two most dominant and significant driving factors affecting the change in the WF_{con} in the LRM and NLRM. Zhao and Chen (2014) obtained similar results and found that the driving factors for the national consumption WF in China were economic activity and population. Moreover, *D* was the third most important and significant factor after *Pop* and *GDP* affecting the WF_{con} of wheat in the LRM, but the result was weaker for the NLRM. In summary, all types of WF_{con} in the net water import regions were positively influenced by GDP and population, whereas they were negatively influenced by technology update (Table 1). There were no consistent contributions by the other influential factors to the WF_{con} of wheat in this study.

All types of WF_{con} in the net water export regions were negatively influenced by technology update and GDP, whereas they were positively influenced by dietary demands (Table 1). The details of the results are described in *Driving influential factors for WF_{con} in the net water export region*, Supporting Information.

Table 1
Influential factors driving the different types of the production and consumption WFs in the net water import and export regions.

	Net water import region							Net water export region						
	T_{min}	T_{max}	P	GDP	Pop	D	Y_{unit}	T_{min}	T_{max}	P	GDP	Pop	D	Y_{unit}
WF_{prod}			L	L, N	L, N	N	L, N				L, N		L,N	L, N
$WF_{prod\ green}$		L, N	L, N	L, N		L, N				L	N		L,N	L, N
$WF_{prod\ blue}$	N	L, N	L		N	L					L, N		L,N	L, N
WF_{con}				L, N	L, N	L, N	L, N				L, N		L,N	L, N
$WF_{con\ green}$		L		L, N	L, N	L, N	N			N	L		L,N	L, N
$WF_{con\ blue}$			L, N	L, N	L, N	L	N				L, N		L,N	L, N

Notes: Blue font indicates positive influence; red font indicates negative influence; "L" is the linear regression model; "N" is the nonlinear regression model.

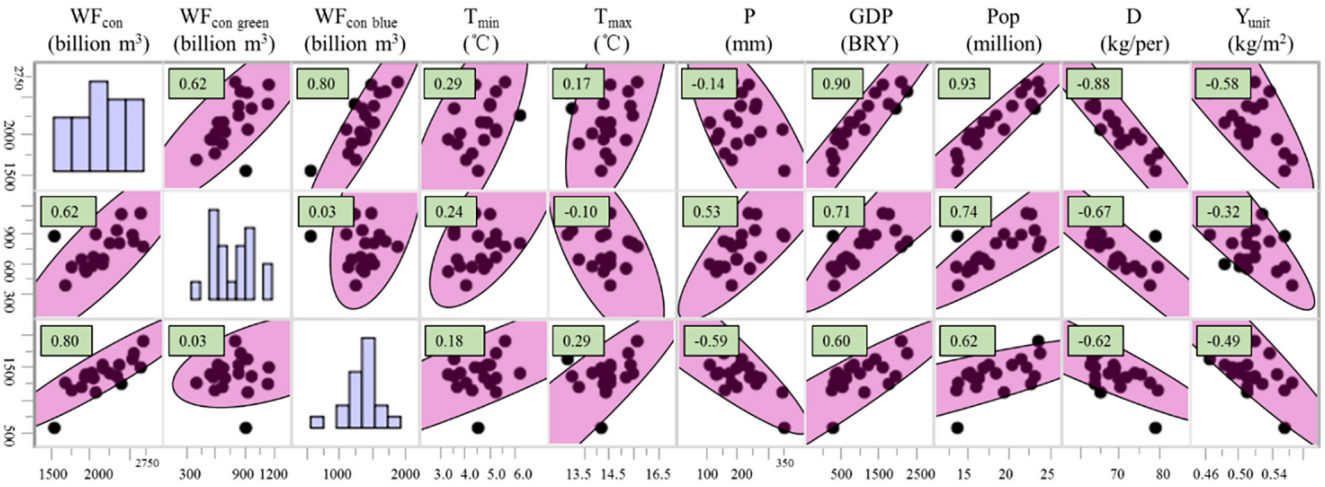

Fig. 3. Correlations between the WF_{con} of wheat (WF_{con}, $WF_{con\ green}$ and $WF_{con\ blue}$) and seven influential factors (average minimum temperature (T_{min}), average maximum temperature (T_{max}) and total precipitation (P) for climate change indicators, gross domestic product (GDP), population (Pop), annual per-capita dietary demand (D), and yield per unit area for technology update (Y_{unit})) in Beijing. The numbers in the green boxes are the correlation coefficients (r) of the two variables.

4. Discussion

Through multivariate and regression analysis, the influential factors were obtained for the changes in the production and consumption WFs of wheat in the water import and export regions. Table 1 summarizes the positive and negative influential factors driving the production and consumption WFs of wheat. In the water import regions, a GDP increase had a strong effect on the change in the WFs, especially for the different types of the consumption WFs. Although rapid economic growth has largely been driven by industrialization, many farmers in remote areas still strongly rely on agriculture for their income. The desperation of these farmers to move out of poverty has accelerated the development of agriculture, which has resulted in a significant increase in the agricultural WFs. Population increase has been another driver for the change in the WFs but has also caused extensive water resource pressure. Despite the successful enforcement of a population control policy in China, the population will increase to 1.436 billion in 2033 owing to population growth inertia (Xu et al., 2013). Thus, the production of sufficient agricultural products remains a priority to support such a large population in the next 10 years. Under the dual pressures of socio-economic development and the increase in population density, environmental issues should also become a greater focus area.

a.

	T_{min} (℃)	T_{max} (℃)	P (mm)	GDP (BRY)	Pop (million)	D (kg/capita)	Y_{unit} (kg/m²)	Int.	R^2
WF_{con} (m³/t)	-45.374* RI=2.21%	85.234** RI=5.54%	-0.748** RI=3.81%	-0.409** RI=21.21%	208.416* RI=51.34%	23.483** RI=8.73%	-3298.673* RI=7.16%	-1696.132**	0.97
$WF_{con\ green}$ (m³/t)	148.635** RI=3.93%	-81.125** RI=2.86%	1.118** RI=3.10%	-1.100** RI=30.99%	351.290** RI=47.03%	59.669** RI=12.07%	16.522* RI=0.02%	-7744.453**	0.87
$WF_{con\ blue}$ (m³/t)	-194.051** RI=7.77%	166.395* RI=8.91%	-1.866** RI=7.84%	0.691** RI=29.50%	-142.891** RI=28.98%	-36.189** RI=11.10%	-3315.846** RI=5.92%	6048.734*	0.87

b.

	T_{min} (℃)	T_{max} (℃)	P (mm)	GDP (BRY)	Pop (million)	D (kg/capita)	Y_{unit} (kg/m²)	Int.	R^2
WF_{con} (m³/t)	0.117** RI=6.93%	-0.097* RI=2.92%	-0.039** RI=3.80%	0.053** RI=14.11%	0.694** RI=41.61%	0.585** RI=19.69%	-0.619** RI=10.94%	16.520**	0.82
$WF_{con\ green}$ (m³/t)	0.227** RI=4.00%	0.134** RI=1.19%	0.648*** RI=18.92%	0.316** RI=24.84%	0.428** RI=29.98%	2.994** RI=7.63%	-2.551* RI=13.44%	2.88E-07*	0.77
$WF_{con\ blue}$ (m³/t)	-0.167* RI=7.66%	0.473** RI=10.91%	-0.503*** RI=8.14%	0.051** RI=25.40%	0.276*** RI=27.81%	-0.261* RI=6.88%	-0.971** RI=13.31%	3622.430**	0.72

Fig. 4. Results of the (a) linear regression analysis and (b) nonlinear regression analysis showing the statistically significant factors for the WF_{con}, $WF_{con\ green}$ and $WF_{con\ blue}$ in Beijing. The green numbers represent the coefficients in the regression equations of the influential factors in the column. Significance levels: *** > 99%; ** 95–99%; * 90–95%. The "RI" values are the relative importance of each selected factor variable of each WF.

Environmental quality is highly correlated with socio-economic development and the interactions between these two aspects should be a priority for decision and policy makers; examples include the "Three Red Line" policy and the "Green GDP" concept in China for example. Dietary demands and technology update largely depended on the increase in GDP and the labor force. The rapid economic growth and urbanization in China over the last two decades have contributed to higher personal incomes, which has resulted in a higher proportion of meat in food consumption (Xue and Landis, 2010). Another common phenomenon is the waste of food in restaurants and home-cooked meals; the average person wasted (consumed) 16 (415) kg of food at home annually, which is equivalent to 40 (1080) kg CO_2, 18 (6 7 3) m^3, and 173 (4956) g m^2 for the carbon, water and ecological footprints, respectively (Song et al., 2015). Strategies for reducing food waste and developing a sustainable diet require information on the impacts of consumption behavior and waste generation on climatic, water, and land resources.

In the net water export region, technology update mainly improved the efficiency and productivity of water utilization in the agricultural sector. The reduction in of irrigation water consumption contributed to large savings in the amount of blue water which could be utilized by other sectors with a better economic output. Although China's water use efficiency in the agricultural sector improved during the study period, the water use efficiency is still lower than that of other industrialized countries due to inappropriate irrigation management practices and unsound investments in infrastructure construction. There is still a large opportunity to further improve China's water use efficiency. The climate indicators did not show consistent contributions to the WFs of wheat in the net water export region, but certainly influenced the WFs of the crop. As shown in Table 1, the three climate indicators significantly influenced the WFs of wheat in Beijing; however, the influence was not significant for the WFs of wheat in Heilongjiang due to the climate in the study areas. It was determined that in China, the climate was the second most important factor after water availability affecting the yield of crops (Piao et al., 2010); for example, warming is believed to be harmful to rain-fed crops but beneficial to irrigated agriculture (Wang et al., 2009). Data from the Chinese National Bureau of Statistics suggested that warming had already enabled a significant northward expansion of rice planting in Heilongjiang from 0.22 million ha in the early 1980s to 2.25 million ha in 2007, i.e., a northward shift from ~48 °N to ~52 °N (NBSC, 2013). In parallel, the rice yield in Heilongjiang has increased from 0.7 million tons to 14.2 million tons over the same period. All these changes suggested that the crop yield in the temperate climate zones of north China has benefited from the increased temperature.

Arable land could also be a potential factor affecting the WFs. Tamea et al. (2014) found that arable land was an overall negative driver for the global virtual water trade. A larger amount of virtual water was exported to trading partners with less arable land (e.g., Norway, Germany, Mongolia, Botswana). The mismatch between arable land and water availability has led to an unsustainable agricultural expansion in semiarid areas of China. Important associated environmental issues include soil degradation, water resource overexploitation and pollution, and land subsidence from groundwater overdraft, all of which threaten ecosystems and human activity (Dalin et al., 2015). Aside from the technology effect, the yield also reflects the quality of local arable land, namely land productivity. Land with high productivity in northern and southwestern China benefits local farmers by providing a higher yield of crops. In order to protect arable land, the Chinese Central Government published the "Soil Pollution Prevention Action Plan" in 2016 to protect the quantity and quality of arable land and limit the overuse of arable land for commercial activities.

An investigation of the provincial agricultural water demand in water import and export regions during 1996–2015 and an in-depth analysis of the influential factors contributing to the changes in the WFs are fundamentally important to decision makers for developing countermeasures and strategic planning implementations to mitigate the water resource pressure in China. The results of the WF accounting and the analysis of the influential factors in this study provide several suggestions to address the water required for agricultural food production and consumption. Climate change results in more extreme rainfall events and higher temperature and requires that human activities are focused on resource saving and environmental sustainability. The combination of conventional and nonconventional water resources from a quantity and quality aspect provides a promising method to supply future water demand and has been widely implement worldwide; examples include the Water Sensitive Urban Design in Australia, the Best Management Practices and Low Impact Development in the United States, and the Sponge City Construction and Development in China. However, water use efficiency improvement is the most suitable method to alleviate the current water stress from a water quantity and water quality perspective. An increase in the water use productivity would result in a reduction in the blue water consumption and water pollution to meet the water demand of other sectors and protect water ecosystems. Last but not least, water saving could also be achieved by importing water-intensive products from other regions or countries, like Beijing and Tianjin. Virtual water strategies of importing products would shift the domestic water resource burden to the other regions and also transfer high productivity products to China. The potential water savings of the international product trade would be considerable if products were exported from water-rich countries to water-scarce countries.

It should also be noted that there are inherent uncertainties in the evaluation and simulation of the production and consumption WFs both in other regions and in the future. The limitations for multivariate and regression analysis were major for the data defection. In addition, the influential factors for other crops and other regions (including water import and export regions) should be analyzed in the future to obtain more reliable statistics on the influential factors affecting the production and consumption WFs. Finally, a future scenario analysis could provide reference data for agricultural water resource management; however, it would be based on assumptions regarding climate change and socio-economic developments. Future studies should be conducted for period of five years and additional parameters regarding climate change, economic and social development in the future. Nevertheless, this study has filled an important research gap by investigating the influential factors affecting the production and consumption WFs in net water import and export regions.

5. Conclusions

This study provides new insights into the influential factors driving the changes in the agricultural WF_{prod} and WF_{con} in net water import and net water export regions. The results indicate that the gross domestic product and population were the dominant positive factors, whereas technology update and dietary demand were the dominant negative factors affecting the changes of in the WF_{prod} and WF_{con} in the net water import region. In the net water export region, technology update was the dominant negative factor affecting the changes in the WF_{prod} and WF_{con}. Climate change did not contribute significantly to the changes in the WF_{prod} and WF_{con} of wheat; however, it was an indispensable factor (especially precipitation for green WF with average relative importance more than 22%; and blue WF with average relative importance more than 15%) affecting the changes in the WF_{prod} and WF_{con}. An in-depth analysis of the influential factors contributing to the changes in the WFs is fundamentally important to decision-makers to develop countermeasures and strategic planning implementations to mitigate the water resource pressure in China.

Acknowledgements

This work was supported by the National Natural Science

Foundation of China [grant number 51779076]; the Foundation for Innovative Research Groups of the National Natural Science Foundation of China [grant number 51421006]; the Fundamental Research Funds for the Central Universities [great number 2018B47814]; the Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD); the Six Talent Peaks Project in Jiangsu Province [grant number 2016-JNHB-007]; the 333 High Level Talents training Project of Jiangsu Province and the National Natural Science Foundation of China [grant number 51509072].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2019.02.051.

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